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Dual-mode round-robin greedy search with fair factor algorithm for relief logistics scheduling

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Abstract

Humanitarian support management is one of the areas of interest after any disaster cases. All the disaster affected regions need relief logistics to improve the suffered people's life. Disaster regions more often have an asymmetric level of relief logistics requirements. Because of this, even distribution of relief logistics to all disaster-affected regions becomes more challenging, particularly in the limited resources scenario. A fair distribution strategy that distributes relief logistics evenly to all disaster regions based on the demand and available resources is vital. This paper applied two basic round-robin based greedy search algorithms and hence proposed an optimized algorithm for fair distribution of relief logistics. The algorithms iteratively regulate distribution schedule in a round-robin fashion with the greedy search from various supply points to the demand regions based on demand, supply, and distance. The optimized algorithm is aimed for fair relief distribution strategy after each round of distribution. The distribution fairness is measured considering minimization of the absolute standard deviation between demand and supply at the demand regions and also considering the number of disaster regions receiving the relief logistics. A benchmark case study, school29 based on the 921 (Chi–Chi) earthquake in Taiwan, has been considered to evaluate the performance of the algorithm. The simulation results show that the proposed algorithm has a fair relief logistics distribution schedules to all disaster regions in the limited vehicle resource scenario.

Keywords

Scheduling; Relief logistics; Fair distribution; Disaster, Greedy Search

1. Introduction

Emergency relief logistics management has been a widespread research area as the disasters occur more often around the world. Disaster instances such as earthquake, hurricane, floods, tsunami, cyclone are striking at different parts of the world. The nature and level of disaster vary from small scale to large scale. These disasters affect people's lives and need a quick response with relief logistics. The main objective of the relief logistics distribution is to provide humanitarian assistance as soon as possible to the areas affected by the disaster. Humanitarian assistance covers different actions such as relief logistics distribution, evacuation, medical support etc. The assistance can be succeeded as long-term and shortterm distribution management covering relief distribution [1]. All these actions have a common goal to support suffered populations in their survival.

A critical and challenging factor of post-disaster management is the distribution of relief logistics such as food, water, medicine, clothes etc. to disaster victims. After the disaster, relief logistics demands are not uniform across the demand regions. It varies from one region to another depending on the suffered population. The study shows most of the relief logistics distribution models incorporate minimization in unmet demand, travel time, cost and even distribution of relief logistics to the disaster-hit areas. Many of the traditional models are mainly concerned with cost minimization ignoring other relevant performance measures such as time of response and the fairness of the distribution operation [2]. Relief logistics distribution plan starts immediately after the disaster. Study on earlier distribution models shows there is no any straightforward model for relief logistics distribution that covers fair distribution operation together with cost and time response [3]. As the disaster regions have asymmetric relief demands, a fair distribution of relief logistics to the disaster region is highly preferred in such scenarios. The Fair distribution operation is concerned with the even distribution of the available limited relief resources to all disaster regions.

This paper applied two basic relief distribution algorithms based on single-mode round-robin and dual-mode round-robin for logistic distribution. We propose an optimized algorithm based on dual-mode round-robin greedy search with a fair factor that compensates the general lack of attention on the even distribution of relief logistics to all disaster-hit regions in limited resources scenarios. The algorithm considers a multi-criteria optimization and improves logistics distribution schedules in a fair way for the limited vehicle resource scenarios.

The rest of the paper is organized as follows. Section 2 presents the some of the previous work reviews on vehicle routing and relief distribution problems along with the problems on limited vehicle resource relief logistics distribution task. Section 3 highlights the proposed relief logistics distribution model for limited vehicle resources based on dual-mode round-robin greedy search. Section 4 shows simulation work and results based on a case study. Finally, conclusion and future works are presented in section 5.

2. Literature Review

Quick response with relief logistics is required immediately after any kind of disasters scenarios through efficient relief logistics distribution. The distribution plan mainly focuses on the relief logistics distribution to each disaster affected regions. Different models such as mathematical, computational, hybrid models with multi-objectives are applied for distribution schedule generation. The distribution schedule and vehicle routing are interrelated issues in the optimized relief distribution scheduling. The vehicle routing also has a significant impact on the distribution strategy. We studied some of the distribution and vehicle routing model and hence analyze the gap on the existing models.

Vitoriano et al. [2] applied an optimized multi-criteria goal programming model that covered some of the aspects of distribution. The model incorporated issues of time of response, cost and equity of the distribution for decision support under relief distribution plan. Sheu [4] presented a hybrid fuzzy clustering optimization model for the operation of emergency relief logistics distribution. For effective distribution plan, the model applied two recursive mechanisms on disaster-affected area grouping and relief co-distribution. Further extension of this model, Sheu applied a dynamic relief-demand management model [5] with multi-criteria decision making to rank groups. The model dynamically allocated relief logistics to the affected areas based on the identified degree of relief-demand urgency associated with those areas. Hu [6] applied an affinity framework for emergency relief scheduling depending on the information of resources available and need. Affinity model was designed with the biological immune concept to represent different components of the distribution process. Based on the affinity model the relief distribution was scheduled. Chang et al. [7] used a greedy multi-objective genetic algorithm for relief logistics scheduling. The model had applied minimization in unsatisfied demand for resources, time to delivery, and transportation costs with adjusted distribution schedules from various supply points. The schedules were generated according to the requirements at demand points. For the limited vehicle resources, the generated distribution sequences did not cover all the disaster points.

Jeon et al. [8] proposed heterogeneous vehicle routing solution from multiple supply points. It adopted vehicle routing problem simultaneously considering heterogeneous vehicles, double trips, and multiple depots by using a hybrid genetic algorithm along with heuristic processes and float mutation rate. Zidi et al. [9] applied multi-agent with a guided genetic algorithm for vehicle scheduling with minimization in cost for disaster relief planning. Lin et al. [10] used the two-phase heuristic approach with temporary supply points around the disaster affected areas to improve in relief logistic distribution efficiency. Vidal et al. [11] presented hybrid genetic search with advanced diversity control for time-constrained vehicle routing. The algorithm applied a concept of a penalty for infeasible routing solutions and also used meta-heuristic to find efficient routes. Finding the optimum vehicle routes are useful for relief distribution in disaster scenarios. Nagata et al. [12] presented a penalty-based memetic algorithm for the vehicle routing problem with time windows. A penalty function was defined to handle the time window and capacity violation. Also, the algorithm applied a population-based heuristic global search combining local search to efficiently handle the time window violation as well as the capacity violation. Özdamar and Yi [13] applied a heuristic greedy l-neighbourhood search technique for identifying a feasible, acceptable solution for the relief distribution process. The heuristic selects partial paths to append to vehicle routes on the basis of the vehicles' utilities. The model constructed all feasible vehicle routes in parallel and iteratively within the vehicles' limited neighborhood for the distribution. In view of these models and methods, an effective optimum scheduling model with even releif distribution is vital for the limited resource scenarios. The effiecient delivery system with limited resources is crucial in the disaster releif plan.

Our previous work [14] used two-phase heuristic search distribution. The model assigned each demand regions with nearest corresponding supply points in the first phase. Demand regions received relief logistics from the assigned supply points as of the availability of resources at the corresponding points. Unmet demands of demand regions after phase one had been supplied from other supply points using bounded heuristic search in the second phase. Minimization of time and unmet demand were the main objectives set for the model. The distribution schedule becomes more crucial when the supply points do not have enough resource to meet the full demand but lack in an even distribution of the relief logistics for the limited vehicle scenarios. Balancing the supply to all the disaster regions becomes more challenging when the supply points do not have enough resources. The demands are mostly asymmetric so some decision criteria must be set to make distribution schedule even to all disaster-hit regions with optimum outcomes. A distribution model with available resources should distribute relief logistics evenly to all disaster-hit regions to support the suffered people. This leads to us to propose an improved relief logistics distribution model to generate an effective schedule to address even distribution. Considering limited vehicle resources, an optimized model is important for a fair distribution of relief to all the regions.

3. Proposed Approach

Considering the limited vehicle resources, we present relief logistics distribution algorithms. We applied two basic distribution algorithms along with a proposed optimized fair relief logistics distribution algorithm. These algorithms apply round-robin greedy search based on distance matrix and demand status to find the nearest demand region from a supply point. Round-robin approach of distribution placed demand regions and supply points in a queue so that each demand regions get chance to be serverd from the supply points on their term. The greedy search provides local optimal choice of distribution based on heuristic at each step. Also, vehicle limitations, multiple source points, demand regions, distance matrix and routing schedules are considered in the formulation of the problem.

3.1 Objective function

The distribution model includes multi-objective functions for the relief logistics distribution with limited vehicle resources at supply points. Three objectives established the for this model are: minimization of unmet demand of resources at all demand regions, minimization of absolute difference in standard deviations of unmet demand and supplied relief and minimization of vehicle travel time for the distribution. Objective functions are set as:

i. Minimization of unmet demand for resources (f1)

   Min f1(RS) = Nc - $\left(\sum_{i=1}^{Nv}\sum_{j=1}^{jxi} f\delta d(rij)\right)$

   Subject to:

   $f\delta d(rij) = 0$, if $\forall i \in V_{TR}$ and $V_{fs}=0$

ii. Minimization of standard deviation of unmet and supplied demand (f2)

Min f3 (RS) = $\sum_{i=1}^{Nv} \mathrm{abs}(SDd - SDs)$

iii. Minimization of vehicle travel time (f3)

Min f2(RS) = $\sum_{i=1}^{Nv} \sum_{j=1}^{jxi} Ti, j \qquad 1 \leq$ jxi≤ kmax

The attributes and variables of the problem model defined where N_c is total relief logistics resources demand, *d* is the resource demand at demand regions (*DR*) and *Nv* is *the* total number vehicles planned in resource scheduling. Variable *rij* defines appointed a number of DRs in resource where the jth mission belonging to the ith vehicles with the attributes of the DR as position d, dx, dy. A function *fδd(rij)* is defined that returns the partial relief received by *rij* demand regions. *kmax* is the maximum missions planned in resource scheduling and *jxi* is the executable missions upper bound assigned for the ith vehicle. In the model, *Tij* is the time spent by the ith vehicle for the jth tour. *SDs* is the standard deviation of unmet demand, *SDs* standard deviation of supply. *DM* ia distance matrix that gives the shortest distance between one point to another. RS is the routing schedule planned with *Vtr (*vehicle tour with single region supply) and *Vfs* (vehicle tour with more than one region with partial supply).

3.2 Single-mode round-robin greedy search (SRRGS) algorithm

A basic single-mode round-robin greedy search (SRRGS) is applied where supply point is selected on the basis of round-robin from the set of supply points for the relief distribution. The algorithm is presented in Algorithm 1. Greedy search is applied to find the nearest demand region based on demand and distance matrix. Demand status of the selected nearest demand region is checked in each round of distribution. For the demand region with no demand, the algorithm applies greedy search to find the next nearest neighbor with unmet demand status. On each vehicle tour, free space check is applied based on the demand of the assigned demand region. 10% is free space is set for the partial distribution. A vehicle with more than 10% free space carries additional relief logistics to the demand region nearest to the assigned demand region based on greedy search. The algorithm generates distribution schedules in each round with maximum possible utilization of the vehicle capacity. The algorithm repeats until the entire available vehicles have been used. This algorithm is simple to implement for relief logistic distribution with multiple supply points and demand regions.

Algorithm 1: SRRGS

```
Read demand status, supply status, vehicle count, distance matrix.
Set threshold = 10% of vehicle capacity
Select supply_point (supply sequence, round-robin)
While (True)
{
    If (vehicle_count [supply_point]  > 0)
   {
      Find_ nearest_ demand_ region (supply_point, distance matrix)
```

```
        If (demand flag (demand_ region) = = 1)
            Find_ next _nearest_ demand_ region (supply_point, distance matrix)
        If (vehicle_freespace > threshold)
        {
          vehicle_tour (demand_ region)
        }
        else
        {
          search ( nearest_ demand_ region (current demand_ region))
          vehicle_tour (demand_ region, partial_tour)
        }
        vehicle_count [supply_point]  --
        resource schedule (demand, supply, resource)
        update (demand, supply, resource)
      if(demand_ region [demand] == 0)
         set demand flag (demand_ region) = = 1
    }
 repeat for all supply_point (round-robin)
}
```

3.3 Dual-mode round-robin greedy search(DRRGS) algorithm

SRRGS algorithm is not able to supply relief to all the demand regions evenly leaving few demand regions with no relief supply for limited vehicles scenario. To overcome this we applied dual-mode round-robin greedy search (DRRGS) algorithm. The algorithm of the developed approach is presented in Algorithm 2. Round-robin of supply point is set as primary mode and round-robin for demand points is set as a secondary mode in the algorithm. On each round, selection of both supply points, demand regions are based on round robin and greedy search is applied for the selection of nearest demand region. Partial distribution strategy is set same as SRRGS algorithm. The algorithm repeatedly supplies relief until all the available vehicles have been used. This algorithm assures a supply of at least some relief logistics to each demand regions in the limited vehicle availability.

Algorithm 2: DRRGS

```
Read demand status, supply status, vehicle count, distance matrix.
Set threshold = 10% of vehicle capacity
Select supply_point (supply sequence, round-robin)
While (True)
{
    If (vehicle_count [supply_point]  > 0)
    {
       Find_ nearest_ demand_ region (supply_point, distance matrix, round-robin)
```

```
          If (demand flag (demand_node) = = 1)
             Find_ next _nearest_ demand_ region (supply_point, distance matrix,round-robin)
          If (vehicle_freespace > threshold)
          {
            vehicle_tour (demand_ region)
          }
         else
         {
            search ( nearest_ demand_ region (current demand_node))
            vehicle_tour (demand_ region, partial_tour)
         }
          vehicle_count [supply_point]  --
          resource schedule (demand, supply, resource)
          update (demand, supply, resource)
        if(demand_ region [demand] == 0)
           set demand flag (demand_ region) = = 1
      }
 repeat for all supply_point & demand_ region (round-robin)
}
```

3.4 Dual-mode round-robin greedy search with fair factor (DRRGSF) algorithm

SRRGS algorithm is not able to supply relief to all the demand regions evenly and DRRGS algorithm supplies relief logistics to all the demand regions but the distribution has not been even to the demand regions. An optimized dual-mode round-robin greedy search with fair factor (DRRGSF) algorithm is proposed for an even relief logistics distribution scheduling. The algorithm is presented in Algorithm 3. Even distribution based on demand and supply of the relief logistics to all disaster-hit regions is the main contribution of the proposed algorithm. For even distribution, a fair factor for all the demand points as a ratio of the difference between original need at demand regions and supply status at those regions to the original need is calculated. The mean fair factor is calculated at the start of each round of distribution. Relief logistics are distributed only to those demand points having fair factor more than the mean fair factor. Supply amount, need status, fair factor and mean fair factor status is updated after each round. Demand points with a fair factor less than the mean fair factor or zero demands are excluded from the demand list search in each round whereas demand regions with fair factor more than the mean fair factor are selected. Greedy search based on distance matrix is applied to find the nearest demand regions having fair factor more than the mean fair factor for each supply point at each iteration. Demand regions are also set to round-robin mode for receiving relief logistics. Partial distribution strategy is set same as SRRGS algorithm with fair factor checks to the nearest region to be selected. The algorithm generates distribution schedules in each round with maximum possible utilization of the vehicle capacity. The algorithms repeat until the entire available vehicles have been used.

3.3 Pseudocode: DRRGSF

```
Read demand status, supply status, vehicle count, distance matrix.
Set threshold = 10% of vehicle capacity
Calculate initial fair_factor (demand_original, supply, demand _node)
Calculate mean_fair_factor(fair_factor, demand_ region)
Select supply_point (supply sequence, round-robin)
While (True)
{
      If (vehicle_count [supply_point]  > 0)
      {
          Find_ nearest_ demand_ region (supply_point, distance matrix, round-robin)
          If (demand flag (demand_ region) = = 1)
              Find_ next _nearest_ demand _node (supply_point, distance matrix,round-robin)
         If (fair_factor[demand_ region] >= mean_fair_factor)
        {
          If (vehicle_freespace > threshold)
            {
              vehicle_tour (demand_ region)
           }
           else
           {
              search ( nearest_ demand_ region (current demand_node))
              vehicle_tour (demand_ region, partial_tour)
           }
           vehicle_count [supply_point]  --
           resource schedule (demand, supply, resource)
           update (demand, supply, resource)
          update fair_factor (demand_ region)
          update mean_fair-factor
        if(demand_ region [demand] == 0)
           set demand flag (demand_ region) = = 1
      }
  }
 repeat for all supply_point & demand_ region (round-robin)
}
```

4. Computational Experiments

To verify the effectiveness of the proposed DRRGSF algorithm, we took the case study benchmark school29 based on the 921 (Chi–Chi) earthquake in Taiwan [7]. Locations of disaster regions and supply points with available connecting links are as shown in Figure 1. The demand regions are connected from the supply points with direct link or with via intermediate links. Location details of demand-regions and supply-points are listed in Table 2. Constraints and assumptions were set as similar as of benchmark school29. Based on the information of suffered population from the disaster regions, relief logistics demands for all regions were calculated. Benchmark school29 set 30% of the total population for relief distribution across 29 disaster points. Relief logistic packages were set as a combination of 1 kg food, 1500 cc of water and 500 gm of other daily necessities. The vehicle capacity was assumed as 4000 kg per vehicle with speed of 40 km per hour. Limited numbers of vehicles available at each supply point are as listed in Table 1.

Table 1: Vehicles availability at supply points

Supply Points	S1	S2	S3	S4
Number of Vehicles	10	22	25	40

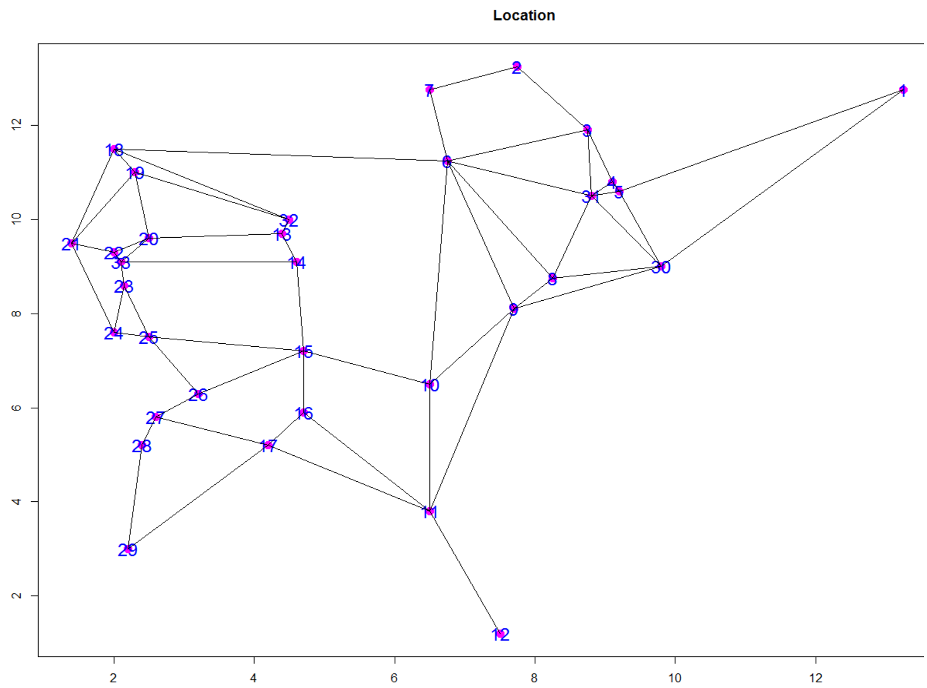

Figure1: Analogous location plot of demand-regions and supply-points along with connecting links of 921 (Chi–Chi) earthquake in Taiwan

Table 2 : Demand-regions and Supply-points list

Point	Location	Node type

1	Jen-Ai school	Disaster-region
2	Pei-Mei school	Disaster-region
3	Pu-Tai school	Disaster-region
4	Pu-Li school	Disaster-region
5	Hung-Jen school	Disaster-region
6	Pei-Shan school	Disaster-region
7	Kuo-Hsing school	Disaster-region
8	Yu-Chi school	Disaster-region
9	Ming-Tan school	Disaster-region
10	Shui-Li school	Disaster-region
11	Hsin-Yi school	Disaster-region
12	Tung-Fu school	Disaster-region
13	Shuang-Wen school	Disaster-region
14	Chung-Liao school	Disaster-region
15	Chi-Chi school	Disaster-region
16	Jui-Feng school	Disaster-region
17	Lu-Ku school	Disaster-region
18	Jih-Hsin school	Disaster-region
19	Tsao-Tun school	Disaster-region
20	Chung-Hsing school	Disaster-region
21	Feng-Ming school	Disaster-region
22	Nn-Tou school	Disaster-region
23	Nan-Gang school	Disaster-region
24	Sa-Kuang school	Disaster-region
25	Ming-Chien school	Disaster-region
26	She-Liao school	Disaster-region
27	Yen-He school	Disaster-region
28	Chu-Shan school	Disaster-region
29	Jui-Chu school	Disaster-region
30	County government police station	Supply-point
31	Pu-Li fire department	Supply-point
32	Chung-Liao fire department	Supply-point
33	County government file department	Supply-point

The simulation was performed on a machine with Intel(R) Core(TM) i5-4590 CPU @3.30 GHz processor with 7.98 GB of RAM running on Windows 7 Enterprise. The performances of the proposed algorithm DRRGSF was compared with SRRGS, DRRGS and Greedy-search-based multi-objective genetic algorithm (GSMOGA) [7]. The resources are distributed form all 4 sources to 29 demand regions Tables 3, 4 and 5 summarize the results of our experiments. For all cases, the absolute difference between the standard deviations for unmet demand and supplied demand were calculated to check the nature of even distribution after generating all vehicle tour. The minimum absolute difference was desired considering a limited number of vehicles available at different supply points. GSMOGA, SRRGS, and DRRGS algorithms had a higher range of absolute standard deviation difference between demand and supply. This indicated uneven nature of the relief logistics distribution. DRRGSF outperforms all these algorithms with the very low absolute difference in standard deviations. DRRGSF had absolute difference only 154.288 whereas GSMOGA, SRRGS, and DRRGS had higher in the range of thousands as shown in Table 3. This reflects DRRGSF algorithm had a more fair distribution of relief logistics to all the demand regions among the discussed algorithms.

Table 3: Standard deviation comparison of GSMOGA, SRRGS, DRRGS and DRRGSF algorithms

Algorithm	Standard Deviation Demand unmet	Standard Deviation Demand supply	Absolute difference
GSMOGA	6153.07	11780.73	5627.70
SRRGS	4889.03	12295.45	7406.42
DRRGS	8039.22	4288.02	3751.2
DRRGSF	5155.72	5310.01	154.29

The effectiveness of DRRGSF algorithm has also been analyzed with other performance measure parameters as shown in Table 4 and Table 5. GSMOGA and SRRGS algorithms distributed relief logistics to only limited disaster regions based on the greedy search leaving some of the disaster regions not receiving any relief as shown in Table 4. DRRGSF algorithm overcomes this issue by distributing at least some relief logistics to all the demand regions. DRRGSF provides more uniform distribution approach considering a number of regions being served.

Table 4: Supply status node count of GSMOGA, SRRGS, DRRGS and DRRGSF algorithms

Algorithm	Number of regions with no supply	Number of regions with full supply	Number of regions with partial supply
GSMOGA	5	21	3
SRRGS	7	19	3
DRRGS	0	15	14
DRRGSF	0	6	23

These four algorithms are also evaluated with the parameter of vehicle capacity utilization as shown in Table 5. The DRRGSF algorithm has maximum utilization of vehicle capacity among all cooperative algorithms in terms of use of available loading volume of the vehicles. These performance measures show DRRGSF is an optimized algorithm for relief logistics distribution with even relief logistics distribution for limited vehicle resources at supply points. The iterative greedy search constructed on the demand and supply amount based on fair factor at each demand region for the distribution schedule has made this approach an optimized approach for relief logistics distribution.

Table 5: Vehicle capacity utilization of GSMOGA, SRRGS, DRRGS and DRRGSF algorithms

	GSMOGA	SRRGS	DRRGS	DRRGSF
Vehicle Capacity Utilization	99.65%	99.51%	95.25%	99.75%

5. Conclusions

This paper has presented relief logistics distribution algorithm for limited vehicle resource scenarios. Two basic algorithms named SRRGS and DRRGS applied and hence an optimized algorithm named DRRGSF is proposed. The algorithm has applied dual mode round-robin with the greedy search to find the nearest demand region for relief logistics distribution. Round-robin selection is applied both for supply points and demand regions with the greedy search for fair distribution. The DRRGSF algorithm used a fair factor of each demand regions and hence mean fair factor as a threshold which iteratively changed in each round based on demand and supply. A comparative study of the experimental results for a case study shows that the proposed DRRGSF gives an even distribution of relief logistics to all disaster regions with respect to other algorithms. With limited vehicles, the proposed algorithm shows a lower range of the absolute difference between standard deviation due to its iterative greedy search based on demand and supply factor at each iteration. This verifies that the fair relief logistics distribution nature of DRRGSF. This algorithm has a clear advantage in terms of serving each region fairly with the limited vehicle availability. Also, it had higher utilization of vehicle capacity for relief logistics distribution. This algorithm can be further enhanced with the heterogeneous vehicle resources at multiple supply points. Other heterogenous goods as per the demand regions need can be added to the relief logostic package with heterogenous logistic distribution nature to deal stochastic demand nature. We will consider multiple capacity and cost of the vehicles as the constraints for the selection of the vehicles.

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